Learning Complex Cell Units From Simulated Prenatal Retinal Waves Using Slow Feature Analysis

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Introduction

The developing visual system is structured and organized even before the onset of vision. Spontaneous neural activity on the retina that spreads in waves has been suggested to play a major role in these prenatal structuring processes [8]. Recently, Albert et al [1] have shown that when employing an efficient coding strategy, such as sparse coding, these retinal activity patterns lead to basis functions that resemble optimal stimuli of *simple cells* found in primary visual cortex (V1).

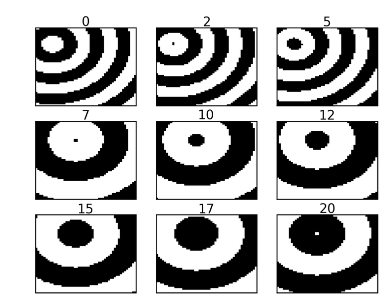
Slow Feature Analysis (SFA) [7] has been successful in reproducing a rich set of *complex cell* features if trained with natural image sequences [2]. Here we present the results of applying SFA to image sequences derived from natural images as well as different models of retinal waves [4]. In order to compare our results with those from classical neurophysiological experiments on V1 cells, we tested the obtained SFA units with sinusoidal gratings of different spatial frequency, orientation, and phase.

Methods

Retinal Wave Models

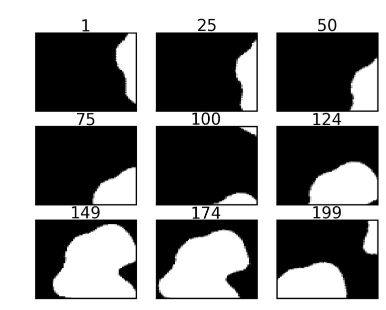
- Radial Waves

Retinal activity is spawned at a randomly chosen pixel and propagates outward in a radial wave front.



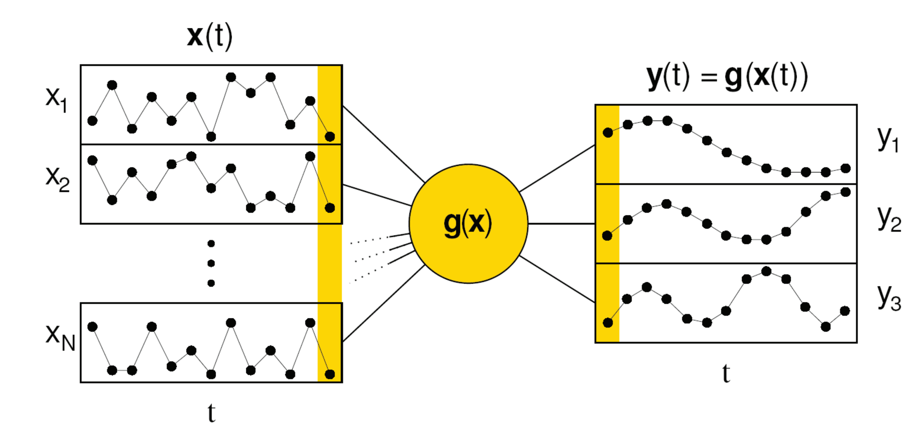
- Godfrey Swindale [4]

Biologically plausible model of retinal waves based on spontaneous activity and activity dependend refractory periods.



Slow Feature Analysis

SFA extracts a slowly varying and decorrelated output signal **y**(t) from a multivariate input signal **x**(t). Learned functions **g**(**x**(t)) are instantaneous transformations, i.e. there is no low-pass filtering.

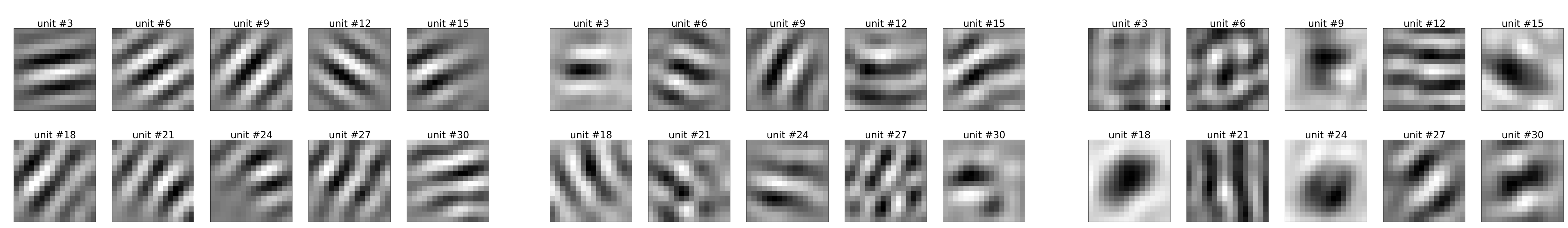


Results

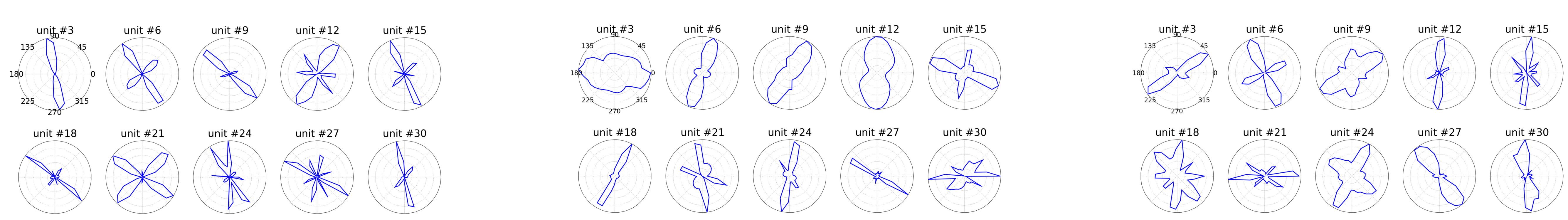
Analysis Methods

Natural Image Sequences | Radial Wave Model | Godfrey Swindale Model

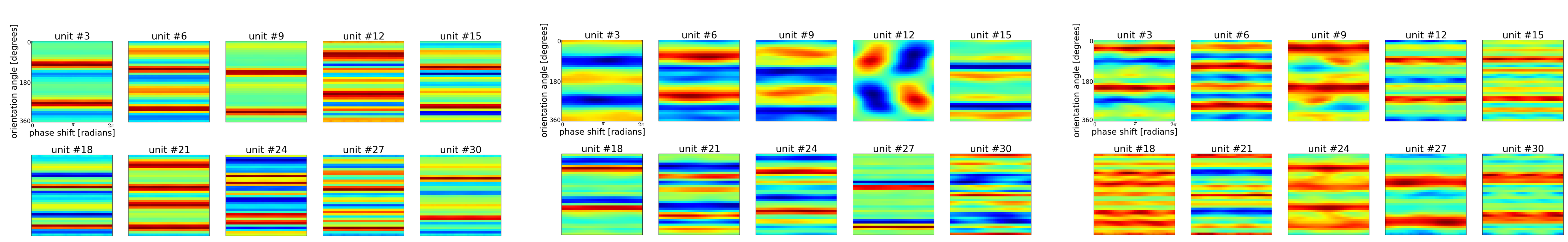
Optimal Stimuli:
We maximize a unit's output under a fixed-norm constraint for the input image, i.e. search in image space for maximal response along the surface of an hypersphere. The stimulus image that elicits the maximal response is plotted.



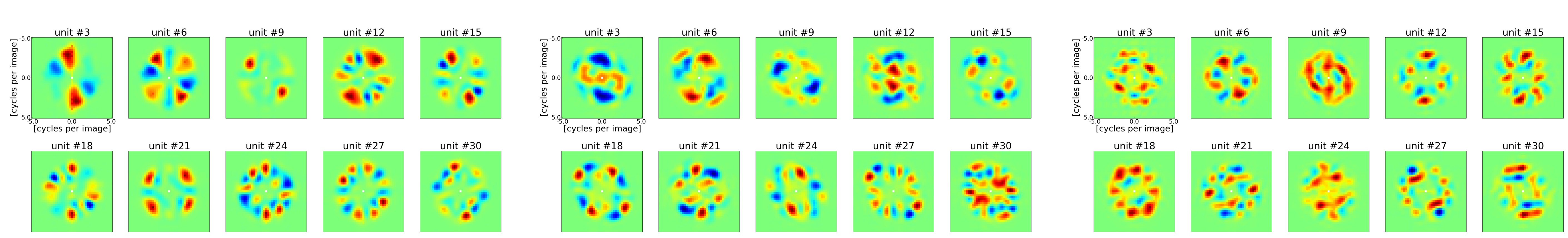
Orientation Tuning:
We present sinusoidal gratings (having prefered spatial frequency and phase) with different orientations to a unit and plot the output versus the orientation angle. Similar to V1 simple and complex cells [6], the SFA units show orientation selectivity.



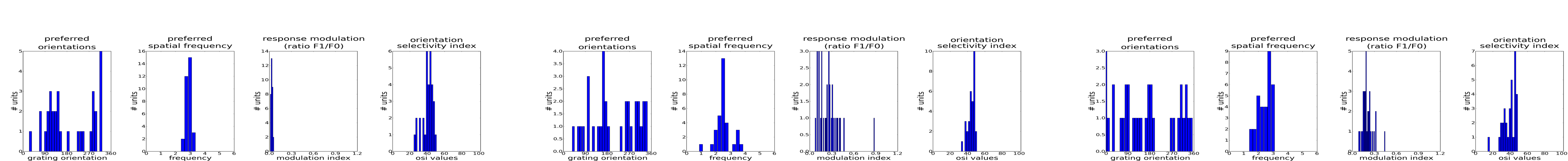
Orientation vs Phase Tuning:
We present sinusoidal gratings (having prefered spatial frequency) with different orientations and phases to a unit and plot the output versus these two parameters. While being selective to orientation, the SFA units are largely invariant to phase, which is the defining feature of V1 complex cells [5].



Orientation vs Frequency Tuning:
We present sinusoidal gratings (having prefered phase) with different orientations and spatial frequencies to a unit and plot the output versus these two parameters. Again similar to V1 complex cells, the SFA units show frequency tuning [6].



Population Statistics:
Histograms of prefered orientation, spatial frequency, response modulation index (F1/F0 ratio), and orientation selectivity index. The majority of obtained SFA units have a F1/F0 ratio that is typical for V1 complex cells [5]. Chapman [3] reported an OSI median for ferret V1 cells (type unspecified) of 39, which compares to our results.



Conclusions

The SFA units obtained share a number of features with V1 complex cells such as orientation- and frequency tuning as well as phase invariance. These features are present when trained with natural image sequences and to a large degree also when trained with models of retinal waves. Hence, retinal waves seem suitable training stimuli to learn invariances and thereby shape the developing early visual system so that it is well prepared for coding input from the natural world.

References

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